MULTIDIMENSIONAL IMAGE CLASSIFICATION BASED ON INFLUENCE CONTROLLERS OF THE CLASSES IN THE IMAGES

Orlando Alves Máximo¹,²
David Fernandes²

¹ Instituto de Estudos Avançados – IEAv/CTA
Rodovia dos Tamoios, km 5,5 – 12228-001 – São José dos Campos – SP, Brasil
oamaximo@ieav.cta.br

² Instituto Tecnológico de Aeronáutica – ITA/CTA
Praça Marechal Eduardo Gomes, 50 – 12228-900 – São José dos Campos – SP, Brasil
david@ita.br

1. INTRODUCTION

The Bayesian statistical approach is a well known technique used in computer based classification, and the Maximum-likelihood Classifier (ML) is one of the most present in literature [1]. In a multidimensional scenario, the structure of the ML Classifier is such that every dimension has the same effect or contribution in the classification process, regardless its quality. If one or more dimensions have poor quality, there's no way to mitigate or eliminate the influence of such dimension in the ML Classifier and a loss of accuracy is expected. In this work a dimension will be associated to an image.

There are several methods to quantify the quality of an image and several ways to use this quality as image influence controller [2, 3].

This paper extend the concept of image influence controller in the Modified Global Membership Function (MGMF) [4] to classes reliability factors in order to use class influence controllers instead a single image reliability factor. A composition of the classes influence controller, provide also the image influence controller.

The estimation of the classes influence controllers is done through the partial kappa coefficient of agreement for each class. In a two dimensional example with SAR images the use of such classes influence controllers achieved better results then the classical ML classifier.

2. THE MODIFIED GLOBAL MEMBERSHIP FUNCTION

As stated earlier, the structure of the ML classifier is such that in a multidimensional case, all the dimensions (images) has the same influence in the classification process. This fact, allied with the multiplicative behavior of the ML classifier, can deteriorate the classification accuracy if one (or more) dimensions have anomalies, because there's no way to mitigate the influence of such dimensions.

In [4], the authors introduced the Modified Global Membership Function (MGMF), that aggregates the image influence controller to control the influence of each image in the decision processes. These factors express the quality or the confidence of each image, with the goal of to increase the influence of the “more reliable” ones and decrease the influence of the “less reliable” in the MGMF. The MGMF can be expressed by:

\[ F_m(X_1, X_2, \ldots, X_N) = p(w_m) \prod_{n=1}^{N} p(X_n | w_m)^{\alpha_n} \]

Where: \( w_m \), \( m = 1,2,\ldots,M \) is the set of reference classes in the images; \( N \) is the number of dimensions and \( \alpha_n \) is the n-image influence controller.

3. CLASSES INFLUENCE CONTROLLERS

In the MGMF, the image influence controllers (\( \alpha_n \)) act in the whole image and all the classes in the image are affected in the same way. Introducing a class influence controller, after some algebra, we can generate a Class Global Membership Function (CGMF) written as:
Where: \( p(X_n) \) is the probability of occurrence of the pixel in the image \( X_n \) and \( \alpha_{nm} \) is the influence controller of class \( m \) present in image \( n \).

There are several approaches used to quantify the quality of the image and how to use it as an influence controller factor. All of them has as objective the accuracy improvement of the classification process. The separability of the classes in an image, the equivocation and the classification accuracy of a single image are examples of possible estimators.

Considering the influence controllers for the image and for the classes presented in the image, we can establish a relationship between them such as \( \alpha_n = f(\alpha_{nm}) \).

We use the following basic conditions: i) all the influence controllers must lie in the \([0,1]\) interval; ii) if all the information classes have the same influence controller, then the image will have the same influence controller too; iii) an image will be considered unreliable (influence controller equal zero) if, and only if, all the classes presented on the image are unreliable too; iv) an image will be considered reliable (influence controller equal one) if, and only if, all the classes presented on the image are reliable too.

With such conditions the relationship between the image and the classes influence controllers can be establish by the arithmetic mean as: \( \alpha_n = \frac{1}{M} \sum \alpha_{nm} \).

5. EXPERIMENTS DESCRIPTION AND RESULTS DISCUSSION

In order to evaluate the impact of the influence controllers in classification accuracy, a set of two 512x512 pixels SAR-580 images (X and L Band) were used. The ground truth was established by five different image analysts using maps and contextual information. Four reference classes were selected in each image.

The ML, MGMF and CGMF classifiers were implemented using IDL® language and compared.

The test sampling scheme was developed using a not-aligned and stratified strategy that allows a well distributed set of samples spread over the whole image. The accuracy of each classifier was estimated using a confusion matrix and the kappa coefficient of agreement. To estimate the class influence controllers we use the kappa coefficient to define the images influence controllers. After that, the classes influence controllers were estimated using the normalized conditional kappa, that will be defined in the complete paper.

Six data sets were used (original images and with a 3x3, 5x5, 7x7, 9x9, 11x11 mean filter pre-processing). Here, we present the results for those that used the original images with a 3x3 and 5x5 kernel mean filter as a pre-processing.

For the 3x3 kernel data set, the image influence controllers, based on the individual accuracy using kappa coefficient were: \( \alpha_1 = 0.389 \) (X Band) and \( \alpha_2 = 0.370 \) (L Band). The classes influence controllers, based on the normalized conditional kappa were: \( \alpha_{11} = 0.091, \alpha_{12} = 0.479, \alpha_{13} = 0.223, \alpha_{14} = 0.764, \alpha_{21} = 0.607, \alpha_{22} = 0.216, \alpha_{23} = 0.189 \) and \( \alpha_{24} = 0.468 \). For the 5x5 kernel data set, the images influence controllers calculated were: \( \alpha_1 = 0.492 \) and \( \alpha_2 = 0.538 \). The classes influence controllers were: \( \alpha_{11} = 0.123, \alpha_{12} = 0.562, \alpha_{13} = 0.327, \alpha_{14} = 0.958, \alpha_{21} = 0.724, \alpha_{22} = 0.386, \alpha_{23} = 0.382 \) and \( \alpha_{24} = 0.660 \).

Table 1 summarizes the accuracies (Kappa coefficient) for the ML, MGMF and CGMF classifiers for the two experiments. The results shown that the MGMF has similar accuracies in comparison with the ML classifier. The CGMF achieved the best performance, of the three classifiers studied.

<table>
<thead>
<tr>
<th>3x3 kernel</th>
<th></th>
<th>5x5 kernel</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>ML</td>
<td>0.565</td>
<td>MGMF</td>
<td>0.537</td>
</tr>
<tr>
<td>CGMF</td>
<td>0.599</td>
<td>ML</td>
<td>0.693</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>0.666</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>0.728</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

7. REFERENCES


